# Deep Learning Framework for Early Detection of Diseases in Plants

**SHORT SYNOPSIS**

*Submitted in partial fulfillment of the requirement of the degree of*

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*By*

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## DECLARATION BY THE SCHOLAR

I hereby declare that the short synopsis entitled **Deep Learning Framework for Early Detection of Diseases in Plants** being submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy in the **Department of Computer Science and Technology** under the **School of Engineering** of Manav Rachna University, Faridabad during the academic year 2024-25.

It is the work that is expected to be carried out under the supervision of **Dr. Parneeta Dhaliwal** and co-supervision of **Dr. Atul Srivastava**. Further, it is declared that the short synopsis is within the plagiarism limit and copy of the same is attached as per the University norms.

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## CERTIFICATE BY SUPERVISOR(S)

This is to certify that, the short synopsis entitled **Deep Learning Framework for Early Detection of Diseases in Plants** is an original piece of work done by research scholar Ms. Shilpa Juneja under the supervision of **Dr. Parneeta Dhaliwal** and co-supervision of **Dr. Atul Srivastava** for the degree of Doctor of Philosophy in the **Department of Computer Science and Technology** under the **School of Engineering** of Manav Rachna University, Faridabad during the academic year 2024-25.

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## ABSTRACT

Plants are essential to the nation's economy and agricultural industry. Therefore, it is critical to care for plants. Plants, like humans, are susceptible to a wide range of diseases caused by bacteria, fungi, and viruses. Early disease detection reduces crop loss rates by allowing for the implementation of preventative measures and appropriate treatments. Deep learning approaches have yielded outstanding results in this field. In this regard, we propose a novel deep learning-based method for improving the likelihood of early detection of plant illnesses. The model was taught using a large number of photos of plant leaves that the user collected depicting illness symptoms. To increase agricultural yields, we recommend taking a comprehensive approach to detecting plant illnesses as soon as possible. The suggested system's effectiveness will be evaluated using a number of measures, including mIoU, f1-score, accuracy, precision, recall, sensitivity, and specificity. Further, the proposed system makes possible a real- time monitoring of diseases in the plants and allows farmers to detect health problems earlier. Additionally, our study also strengthens the growing field of computer- vision based agricultural research and shows how deep learning approaches might help in increasing speed with accurate results in the important field of crop disease detection.

**Key words**: Agriculture, Deep learning, Convolutional Neural Networks, Real-time disease detection, Plant leaves dataset.

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## INTRODUCTION

One of the most crucial industries to the survival of humanity is Agriculture. In nations like India, where agriculture either directly or indirectly supports the economy, it is a vital sector. It focuses on the requirement of nurturing plants from seedlings till the desired crop is produced. Preserving the crop from numerous diseases is a critical concern, as these diseases can prevent the crops to grow completely. Plant diseases have the great potential to completely destroy species variety resulting in large losses in food production. Manual monitoring of disease detection is possible, but it is a tedious and hard procedure. Farmers and specialists have been using the leaves of plants to spot diseases with their naked eyes for centuries. This approach necessitates field experience and competence. Farmers lack this expertise. Inadequate funding also prevents them from hiring experts who can identify the disease, resulting in ineffective disease control and reduced agricultural yield. Plant diseases must be identified and treated as soon as possible to improve productivity, yield, and agricultural profits. Farmers may benefit from digitalizing the process of identifying and classifying illnesses. Without a doubt, deep learning is the best approach for identifying plant diseases in the current era. After obtaining the affected plants, disease-specific labels are applied to them. These images are converted into pixels to provide additional information.

Using automatic feature extraction, neural network models automatically categorize images into classes. Following the extraction of features, the best subset of features is chosen, and one of the classification algorithms is used. In the field of plant disease identification, it has been seen that the earlier feature extraction-based algorithms are less accurate and efficient. One of the remarkable approaches for object identification in deep learning is the Convolutional Neural Network (CNN). CNN is frequently used for speech recognition, natural language processing, object identification, video processing, segmentation, and image classification. Convolution layer, Pooling layer, Fully Connected layer and non- linear layer make up CNN's four layers. By collecting the essential information from the input image, the convolution layer employs kernel filters to calculate the convolution of the image. Two successive convolutional layers are combined at the pooling layer. The fully connected layer, sometimes referred to as the convolutional output layer, is the third layer. A neural network's output, such as "yes" or "no", is determined by the activation function. Pooling and non-

linearity are parameter- free, while convolutional and fully-connected layers are. CNN performs exceptionally well in solving machine learning problems. Particularly in the image-related applications- like computer vision - the results are remarkable. By capturing plant leaf images and feeding them to a model, one of the best techniques to determine whether the plant has a certain disease or not is CNN.

Early plant disease detection is totally transformed by AI's data analysis capabilities, especially in the computer vision tasks. AI algorithms easily locate minor abnormalities that indicate the existence of disease, prior to the appearance of symptoms, by looking into vast number of plant images. AI techniques in agriculture can save labor expenses, eliminate time wastage, and improve crop quality and production overall.

## LITERATURE REVIEW

Ma et al. [1] employed a CNN model to identify four cucumber diseases: powdery mildew, downy mildew, anthracnose, and target leaf spots. Achieved detection accuracy was 93.4%. A faster R-CNN structure was presented by Ozguven et al. [2] to enable the identification of the beetroot disease known as Leaf Spot. A total of 155 images were trained and tested. The results show that the overall correct classification accuracy of this method is 95.48%.

To identify grape leaf diseases such as Black Rot, Leaf Blight, Mites, and Black Measles, Xie et al. [3] proposed a model called Faster DR-IACNN, which combines the Inception-V1 module, SE, Inception-V2 module, and Faster R-CNN detection technique. The Grape Leaf Disease Dataset was used for the investigation. This study extracted more features more efficiently, with a mAP of 81.1%.

Sharma et al. [4] proposed a deep learning based multi-classification model.The suggested work is innovative in that it takes a different approach from previous crop detection studies that focus on the classification of Mustard Downy Mildew (MDM) disease on the basis of its severity, achieving remarkable accuracy. This model has been trained on a vast amount of real-time image dataset consisting of 1500 images captured in the fields of Rajpura province in Punjab, India. The study took into consideration four distinct degrees of illness severity which are as follows-a) Initial Degree (ID) b) Medium Degree (MD) c) Half-way risk degree (HWD) d) High-risk degree (HRD). In binary classification, 95.6% detection accuracy was obtained using healthy and diseased crops, while 96.66% detection accuracy was obtained using High-risk degree (HRD) severity degree.

A convolutional neural network model was developed by Nigam et al. [5] to identify plant diseases based on images of wheat crops with yellow rust and healthy leaves. With a 97.3% testing accuracy, the CNN architecture-based model distinguished between leaves that were healthy and leaves that had yellow rust. The model was trained using a total of 1212513 parameters. The model's noticeably high success rate makes it suitable for image-based disease identification.

A model based on convolution neural networks was proposed by Patil et al. [6] to identify illnesses that impair the well-being and development of tulsi plants. Numerous ailments are treated with tulsi as an herbal remedy. Using a self-created database, a range of images of Tulsi leaves were gathered for this study, which produced a 75% accuracy rate.

Hridoy et al. [7] suggested a deep CNN called MPNet in which a dataset of 47760 images of leaf ,stem and pod of mustard plant consisting of nine classes was created with the help of eleven image enhancement approaches to detect six types of diseases namely, White Rust, Leaf Spot, Blackleg, Fusarium Wilt, Stem Rot and Pod Spot. MPNet achieved 97.11% accuracy on recognizing 2388 test images. Its performance is compared against four most advanced CNNs: MobileNetV2, DenseNet121, VGG19, and ResNet50. Among these, MobileNetV2 achieved highest testing accuracy of 92.83%.The results indicate that MPNet has the potential to significantly improve mustard cultivation in the long run and is capable of correctly diagnosing diseases that impact the plant.

A deep residual network model with transfer learning, known as G-ResNet50, was proposed by Wenchao et al. [8] to identify and categorize three strawberry diseases: powdery mildew, anthracnose, and leaf spot. During the training phase, the CNN model's convolutional and pooling layers received weight parameters that were pre-trained from the ResNet50 model. PlantVillage was the dataset used. The G-ResNet50 model outperformed other models with an accuracy of 98.67%, according to the model's results.

In order to classify plant diseases, Tabbakh et al. [9] presented a hybrid model of transfer learning and vision transformers called TLMViT. Three contaminated crops- bell peppers, potatoes, and tomatoes –were recognized by this model. Three classes from the Wheat Rust Dataset and fifteen classes from the PlantVillage Dataset were used to collect leaf images. Plant diseases are accurately classified by TLMViT; on the PlantVillage and wheat datasets, it achieved an accuracy of 98.81% and 99.86% for VGG19 and the ViT model, respectively.

An enhanced MobileNetv3 model was proposed by Bi et al. [10] to identify the following corn diseases: mild corn, dwarf mosaic virus, rust, northern leaf blight, and gray spot. The purpose of dilated convolutions was to expand the receptive fields. The accuracy of the model was 98.23%, according to the results.

Using a model named EfficientNet, Rajeena et al. [11] identified the following common corn diseases: Fusarium Ear Rot, Gray Leaf Spot, Goss's Wilt, Southern Corn Leaf Blight, and Northern Corn Leaf Blight. The accuracy of this model was 98.85%, according to the results.

Kukreja et al. [12] proposed a hybrid model that combined a long short-term memory(LSTM) and Convolutional Neural Network (CNN) to identify 3000 images of mustard crops according to the six severity levels of the disease known as Mustard Downy Mildew: healthy, extremely low, low, moderate, high, and extremely high. The model was trained on a total of 2400 images, 400 images for each class, and validated on 600 images, 100 images for each class. The method of training was carried out with a batch size of 32 for 50 epochs. The entire dataset for testing was divided into 70:30 training and validation half. The recommended CNN-LSTM hybrid model achieved a high overall accuracy of 92.36% in determining the severity of mustard downy mildew.

A comparative analysis of various deep learning techniques with their results and limitations has been shown in the Table 1.

| **Sr No** | **Model/ Algorithm** | **Plant** | **Disease** | **Methodology/ Method** | **Result (Accuracy)** | **Limitations** |
|---|---|---|---|---|---|---|
| 1. | Deep CNN [1] | Cucumber | Target Leaf Spot, Downy Mildew, Powdery Mildew, Anthracnose | 1)Collection of Dataset<br>2)Preprocessing of images<br>3)Applying Deep CNN<br>4)Evaluation of | 93.4% | Low accuracy |

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| | | | | DCNN | | |
| 2. | GoogLeNet and Cifar 10 [13] | Maize | Curvularia leaf spot, Rust, southern leaf blight, dwarf mosaic, Gray leaf spot, round spot, Brown Spot Northern leaf blight | 1)Dataset Collection 2)Image Augmentation 3)Applying Deep CNN 4)Evaluation of DCNN | 98.9 % | More types of maize diseases identification needed |
| 3. | AlexNet with Transfer Learning [14] | Grape and Mango | Grape Diseases- Blight, Black Measles, Black rot Mango Diseases- Bacterial Canker, Powdery Mildew, Scab | 1)Image acquisition 2)Image Processing 3)Image Segmentation 4)Classification and Detection using AlexNet 5)Android Application 6)Identification of Abnormal and Normal Disease 7)Disease identification | Mango leaves- 89% Grape Leaves- 99% | Low accuracy in the identification of mango leaf diseases and model misclassified the images into other classes in some instances. |
| 4. | Multi-layer CNN [15] | Mango | Anthracnose - | 1)Image Acquisition 2)Preprocessing(C | 97.13% | Inconsistencies encountered |

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| | | | | ontrast Enhancement and Resizing)<br>3)Separating images into training and testing dataset<br>4)Training and testing with CNN<br>5)Validating the performance and comparing with other CNN approaches | | when working with real-time dataset |
| 5. | Capsule Network with Convolution layers [16] | Peanut | Net Blotch, Rust, Brow Spot, Black Spot, and Anthracnose | 1)Construction of dataset<br>2)Data Preprocessing<br>3)Applying Capsule network<br>4)Adding convolution layers to the capsule network<br>5) Evaluation and comparison of results | 83.58% | Disease detection was difficult because of the overlapping of diseased leaves |
| 6. | Faster R-CNN and | Rice | Bacterial blight, Rice | 1)Collection of images from the | Rice Blast- | Real time monitoring |

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| | FCM-KM [17] | | blast and sheath blight | field 2)Image preprocessing based on 2DFM-AMMF 3) Image Segmentation processing based on Faster 2D-Ostu 4) Detection of Rice disease | 96.71% Bacterial Blight-97.53%, Sheath Blight-98.26% | need to be realized |
| 7. | UnitedModel [18] | Grape | Isariopsis leaf spot , Esca and Black Rot | 1)Collection of dataset 2)Dataset Preprocessing 3)Applying UnitedModel 4) Evaluating the performance | 98.57% | |
| 8. | Deep Neural Network with APGWO Feature Selection approach [19] | Mango | Anthracnose, Gall Midge, Powdery Mildew | 1)Dataset Collection 2)Image Preprocessing 3)Applying approach with CNNs 4) Feature Extraction for ANN approach | 89.41% | Low accuracy, not effective for diverse dataset |

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| | | | | 5) Applying APGWO<br>6)Validating the performance | | |
| 9. | ResNet and VGG [20] | Apple | Cedar Rust, Black Star, And Apple Grey-Spot Disease | 1)Dataset collection<br>2)Feature Extraction and Classifier<br>3)Training of CNN<br>4)Result Evaluation | 98.5% by ResNet | Less number of diseases covered |
| 10. | EfficientNet and DenseNet [21] | Apple | Scab, Rust and Multiple Diseases | 1)Dataset Acquisition<br>2)Data Preprocessing<br>3)Exploratory Data Analysis<br>4)Model Building and Training<br>5)Model Testing | EfficienNet-99.8% and DenseNet - 99.75% | Robustness required, more accuracy can be achieved by various ensembling techniques |
| 11. | Deep CNN [5] | Wheat | Yellow Rust | 1)Dataset Collection<br>2)Splitting data into Training and Testing dataset<br>3)Image | 97.37% | Only one disease considered, accuracy is low comparativel |

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| | | | | Preprocessing<br>4)Applying CNN<br>5)Evaluating results | | y |
| 12. | Transfer Learning, Fine Tuning, and ResNet 50 [22] | Grape | Esca Black measles disease | 1)Read RGB Image<br>2)RGB to HSV Conversion<br>3) K- Means Clustering on Saturation Channel for Segmentation of leaf from Background<br>4)Classification using Res-Net 50 | 100% | - |
| 13. | Deep-Learning based Multi-classification model [4] | Mustard | Downy Mildew disease | 1)Collection of the real-time dataset<br>2)Preprocessing of collected dataset<br>3)Setting up Experiment<br>4)Model Proposed<br>5)Result Evaluation | 96.66% | Low accuracy, dataset contained less number of images |
| 14. | G-ResNet50 [8] | Strawberry | Powdery mildew, | 1)Dataset Collection | 98.67% | No consideration |

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| | | | Strawberry Anthracnose, Leaf Spot | 2)Image Preprocessing<br>3)Splitting dataset into training, verification, and testing<br>4) Appling G-ResNet50<br>5) Validating the performance | | of the relationship between the model network structure and model parameter optimization. There is requirement of new network models and optimization methods. |
| 15. | OSOS-AResNet-50 [23] | Citrus, Guava, Mango and Eggplant | 15 different classes | 1)Image dataset collection and preprocessing<br>2)Applying AResNet-50<br>3)Efficacy Evaluation<br>4)Comparison with different CNN models | 98.20% | - |
| 16. | AT- AlexNet model [24] | Corn | 6 diseases | 1)Collection of data<br>2)Data Preprocessing | 99.35% | Less sample size and disease types |

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| | | | | 3)Applying AT-AlexNet model<br>4)Evaluating the results | | |
| 17. | MPNet[7] | Mustard | 6 diseases | 1)Creating Mustard plant Dataset<br>2)Resizing the images<br>3)Applying MPNet<br>4)Result Evaluation<br>5)Comparison with state-of-art CNN models | 97.11% | Low accuracy, other classes of mustard plant can be added |
| 18. | CNN with 2 Convolution and Max Pooling Layers [6] | Tulsi | Fusarium Wilt, Powdery Mildew, Tulsi shoot blight | 1)Collection of Dataset<br>2)Data Classification<br>2)Data Preprocessing on training data<br>3) Applying CNN with 2 Convolution and Max Pooling Layers<br>4) Disease Pre | 75% | Low accuracy, less number of images considered |

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| 19. | EfficientNet [11] | Corn | Leaf Blight, Gray Leaf Spot, Northern Corn Leaf Blight, Goss's Wilt , Southern Corn Fusarium Ear Rot | 1)Dataset Collection 2)Data Preprocessing 3)Feature Extraction 4)Classification using EfficientNet 5)Performance Evaluation | 98.85% | Small dataset used, some diseases not included in the dataset |
| 20. | Vision Transformer model with Transfer Learning (TLMViT) [9] | Bell Pepper, Tomato, Potato | Mosaic, Yellow leaf Curl, Target Spot, Septoria Leaf Spot, Early Blight, Leaf Mold, Late Blight, Spider Mites, Bacterial Spot, Yellow Rust, Brown Rust | 1)Data Acquisition 2)Image Augmentation 3)Feature Extraction using pre-trained model and ViT model 4)Classification using MLP classifier | 98.81% on PlantVillage Dataset and 99.86% on Wheat dataset | More training and fine tuning the weights in the first phase of feature extraction for particular crops needed |
| 21. | Improved MobileNetv3 (CD-MobileNetv3 | Corn | Northern Leaf Blight, Gray spot, Dwarf | 1)Collection of dataset 2)Data Preprocessing | 98.23% | Disease detection in field environment |

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| | ) [10] | | Mosaic virus, Mild Corn, Rust | 3)Applying Mobilenetv3<br>4)Applying CD-Mobilenetv3<br>5)Result evaluation<br>6)Comparison with other DL models | | is more challenging |
| 22. | Hybrid model: CNN and Long Short-term Memory Model [12] | Mustard | Downy Mildew Disease | 1)Collection of real time datasets<br>2)Data Preprocessing<br>3)Splitting dataset into training and validation proportions<br>4)Applying hybrid model on training data<br>5)Classification of data into six degrees of disease severity | 92.36% | Low accuracy, Small dataset, More diseases could be considered |

**Table 1: Research work done by researchers with the results in terms of accuracy and their limitations**

## DESCRIPTION OF BROAD AREA

The applications of artificial intelligence (AI) and machine learning have grown substantially in this modern era. Nonetheless, since artificial intelligence emerged as a viable alternative, scientists have worked on the problem of plant disease diagnosis. Furthermore, the capability of artificial intelligence, particularly machine learning, has enabled the early detection of plant diseases. Consequently, several procedures related to machine learning were implemented in this domain, and their drawbacks prompted the development of deep learning. Deep learning, by the way, is a type of machine learning. It is a popular research topic among academicians because it extracts characteristics from images, making it useful for image processing applications such as object recognition, etc. It is also used to analyze complex patterns found in data. The ability of deep learning techniques to identify plant diseases leads to the development of new techniques that remove artificial limitations in the selection of disease spot features and improve the objectivity of extracting plant disease features. They have an ability to detect small changes that point to the existence of disease.

Many AI models based on image analysis have been suggested in recent years for the automatic detection of diseases in plant leaves. Deep learning models, specially, Convolutional Neural Networks (CNN), have shown outstanding potential in the identification and classification of plant diseases automatically from images. CNN is made up of mainly three layers: Convolutional layers, pooling layers, and fully connected layers. Image- based pattern recognition is basically done by CNN. That is why, CNN is preferred in the detection of plant leaves diseases irrespective of whether the leaves are healthy or diseased. Ultimately, one of the most powerful tools in the modern agriculture is the plant disease detection based on AI, which guarantees fast response and crop production maximization. Convolutional Neural Networks (CNN) have shown to be incredibly efficient for various visual categorization tasks because of its learning complex patterns capability. By analyzing visual symptoms like changes in color, structural alterations, these models will be able to instantly identify healthy and unhealthy plants. In addition to providing effective and timely disease detection, AI also aids in preventing plant disease transmission. These models show outstanding results in recognizing patterns and collecting specific details from statistics, like growth abnormalities, changes in color etc. that might indicates an infection.

The real strength of AI lies in its capability to analyze vast visual input quickly. Rapid detection of diseases in plant leaves helps farmers to quickly spot specific treatments. This not only shields the crops and gives them the capability to take preventive actions to reduce losses and raise yields. Moreover, it gives immense benefit to both the farmers and the environment. With AI technology developing in a rapid pace, detecting plant diseases tends to be more vital in preserving the world's food supply.

Plant disease diagnosis is completely transformed by artificial intelligence, which provides sophisticated data-driven methods to enhance the accuracy and speed of crop disease identification. Plant diseases are preventable and controlled by early detection, which is also crucial for effective agricultural production management.

## OBJECTIVES OF THE STUDY

- To do a literature review of the various existing techniques for disease detection in plants.
- To create our own plant dataset of healthy and infected plants.
- To propose a novel technique for disease detection in plants, achieving better performance.
- To develop an ensemble system for timely detection of infection in plants.

## METHODOLOGY TO BE ADOPTED

- Collection of dataset.
- Pre-processing of dataset.
- Splitting into training and testing dataset.
- Propose a new deep learning model.
- Training the proposed model using the training dataset.
- Performance evaluation based on various performance metrics.

## EXPECTED OUTCOME OF THE RESEARCH

**1) Improving the accuracy of disease diagnosis:**

The main goal is to identify diseases affecting crops more accurately as compared to the existing techniques.

**2) Creating and expanding the dataset:**

Create or collect a dataset containing images of healthy and diseased leaves. The variety and size of the dataset can be increased with augmentation techniques, which are crucial for developing powerful deep learning models.

**3) Paper Publications:**

Research on deep learning frameworks for early detection of plant diseases facilitates us to present 2 Conference Papers and publish 3 Journal Papers.

The purpose of the research is to improve agricultural productivity and protect crops by developing more accurate, effective and scalable methods for identifying crop diseases.

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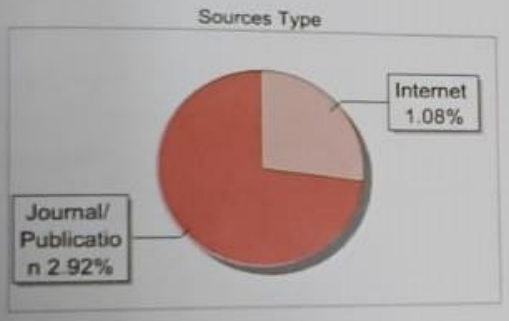


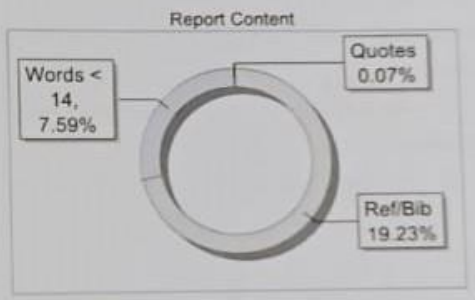


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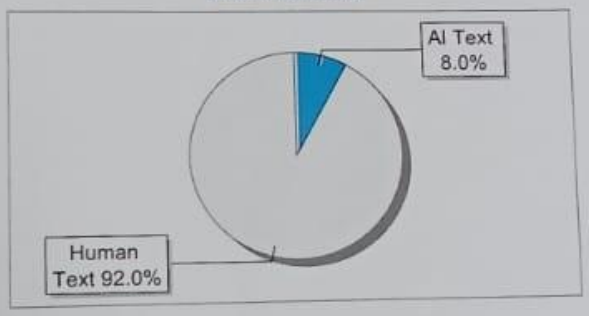


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